IJRFM Volume 4, Issue 7 (July 2014) (ISSN 2231-5985)
IMPACT FACTOR:4.088

EXISTENCE OF PERSISTENT TEMPORAL DEPENDENCE IN ASIAN EMERGING MARKETS EXCHANGE-TRADED FUNDS (ETFS)

Cheng-Wen Lee*

John Francis Diaz**

Truong Hongngoc***

ABSTRACT

This research investigates the existence of persistent temporal dependence in the returns and volatility of seven Asian emerging market (EM) exchange-traded funds (ETFs) from 2008 to 2013 using fractionally-integrated models. This paper finds that SPDR S&P China ETF (ticker: GXC) and Wisdom Tree Indian Rupee Fund (ICN) ETFs have intermediate memory, which characterizes the strong tendency of these ETFs to mean revert. This study also finds long memory properties in the volatility structures of most Asian EM ETF, which is a possible sign of market inefficiency, and can be exploited by financial traders in the long-term through a "hold" strategy to earn excess returns. Moreover, the log-likelihood values point to the ARFIMA-HYGARCH models as the best fitting models compared to the ARFIMA and ARFIMA-FIGARCH models.

Keywords: *Asian emerging markets, exchange-traded funds, long-memory models*

JEL Codes: G11 and G17

*Professor, Department of International Business, Chung Yuan Christian University, Taiwan, R.O.C.

**Assistant Professor, Department of Finance, Chung Yuan Christian University, Taiwan, R.O.C.

***Ph.D. Program in Business, College of Business, Chung Yuan Christian University, Taiwan, R.O.C.

1. INTRODUCTION

Emerging markets (EMs) have experienced rapid development and industrialization in the past decade; and investments tracking the performance of EMs are projected to continue its growth path in the next two decades. Based on the Goldman Sachs global economic report, EMs' equity capitalization could expand from $14 trillion in 2010 to $37 trillion in 2020 and $80 trillion in 2030. Hence, identifying the predictable properties of EM investments returns is important and has long been a great interest for academicians and investors alike, because of the huge potential that EM economies are offering. The persistent temporal dependence in financial time-series or the more popularly known long-memory process provides explanation on the predictability of returns and volatility of a particular data series. The studies of Assaf (2006), Floros et al. (2007) and Kang and Yoon (2007) are some examples of literature discussing the presence of positive dependence in the financial data of emerging markets (EMs). According to Bekaert and Harvey (2000), EMs experience high volatility, high risk in comparison to developed markets, but offer high rates of returns as well as low correlation with developed markets.

One type of investments that are flourishing and closely tracking EM markets are the exchange-traded funds (ETFs). These investment channel have been in existence for over twenty years now since State Street Global Advisors (SSgA) launched the SPDR (Standard & Poor's Depository Receipts), the first ETF in January 1993. ETFs replicate the performance of stock indices, fixed income, bonds, commodities, real estate, currency, investment strategies and international markets. This research focuses on seven ETFs tracking Asian EMs. These ETFs are designed to track the performance of Asian financial markets on a daily basis. Understanding the dynamic behavior of Asian EMs is crucial for portfolio managers, and even researchers, because financial markets of emerging countries are becoming a major channel of global portfolio diversification.

The long-memory process is one of the major econometric processes that has experienced high applicability to financial time-series and has become a part of investment strategies and portfolio management over the last three decades. Granger and Joyeux (1980), and Hosking (1981) introduced the fractionally-integrated autoregressive moving average (ARFIMA) in the early 1980s. Baillie et al. (1996) expanded the model in the middle of the 1990s to capture the conditional variance through the fractionally-integrated general autoregressive conditional heteroskedasticity (FIGARCH) model. Davidson (2004) further improved the model in the middle of the 2000s by the introduction of the hyperbolic general autoregressive conditional heteroskedasticity (HYGARCH) model. The big improvement that the fractional integration long-memory models offered is allowing the difference parameter to be a non-integer, which provides more flexibility to the conventional whole number integration parameters of the integrated autoregressive moving average (ARIMA) and general autoregressive conditional heteroskedasticity (GARCH) models. The advantage of the fractional integration models over the conventional ARIMA and GARCH models have been shown in numerous financial time-series literature like stock returns (Chen and Diaz, 2014; Tan and Khan, 2010), exchange rates (Nouira et al., 2004; Beine et al., 2002), commodities (Choi and Hammoudeh, 2009; Kyrtsou et al., 2004), and ETFs (Chen and Diaz, 2013; Rompotis, 2011).

This research is interested in applying long-memory models to seven Asian EM ETFs. This paper was motivated by the limited literature determining persistent temporal dependence in the returns and volatility of these types of

ETFs, particularly in determining the varied ranges of predictions, (i.e., short-, medium- and long-memory), and effects of shocks that help in determining the predictability of financial time-series. This research contributes to the Asian EM literature by applying three long-memory models, namely, a) ARFIMA, b) ARFIMA-FIGARCH, and c) ARFIMA-HYGARCH models in examining long-term positive dependence in the returns and volatility of Asian EM ETFs. This paper proposal will differ from the previous studies through these four main objectives: a) determine positive long-term dependence in the time-series of Asian EM ETFs, and examine the dual long-memory process in their returns and volatilities; b) look for differences in the characteristics of each ETFs with regards to their short-, intermediate-, and long-memory processes; and lastly c) challenge the basic assumptions of the efficient market hypothesis (EMH) of Fame (1970), because the presence of high-order positive correlations make predictions on future returns possible.

The EMH provides explanation on the impossibility of forecasting financial instrument returns. However, through the utilization of long-memory models, this paper will try to present conclusions about Asian EM ETFs that may dispute the weak-form efficiency hypothesis. A number of literatures (Wright, 1999, Bekaert and Harvey, 1995) have already claimed that developed markets are more efficient, and EMs show more signs of market inefficiency. The possible long-memory property present in Asian EM ETFs can be exploited by investors and portfolio managers to earn excess returns. The findings can also offer academicians and researchers additional future channels research about the properties of these types of ETFs.

The research is written as follows. Section 2 explains the data and methodology; Section 3 shows the empirical results; and Section 4 presents the conclusion.

2. DATA AND METHODOLOGY

The study utilizes daily closing prices of the seven Asian EM ETFs, namely, iShares MSCI Malaysia Index Fund (ticker: EWM), SPDR S&P China ETF (GXC), Wisdom Tree Indian Rupee Fund (ICN), Market Vectors Indonesia Index (IDX), Market Vectors Russia ETF (RSX), iShares MSCI Thailand Investable Market Index Fund (THD), and Market Vectors Vietnam ETF (VNM). The data were extracted from the Yahoo! Finance website. Study periods begin with the varying inception dates of ETFs until December 31, 2013. The series of returns were computed as, $y_t = 100(\log p_t - \log p_{t-1})$, where p_t represents the ETF price at time t. The financial time-series data were modeled by ARFIMA, FIGARCH and HYGARCH processes and are explained below.

The ARFIMA model was developed by Granger and Joyeux (1980), and Hosking (1981) to introduce the modeling of the long-memory process. The model was first to allow the differencing parameter to be a non-integer, and consider the fractionally integrated process $I(d)$ in the conditional mean to model the returns. The ARFIMA (p,d,q) model has both stationarity and invariability conditions and can be written as:

$$\phi(L)(1-L)^d (X_t - \mu) = \theta(L)\varepsilon_t \tag{1}$$

$$\varepsilon_t = z_{t\sigma_t}, \quad z_t \sim N(0.1), \tag{2}$$

Where $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - ... - \phi_P L^p$ and $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - ... - \theta_P L^p$ represent the AR and MA polynomials, respectively; d denotes a fractional integration real number parameter, L represents the lag operator and ε_t denotes a white noise residual. The $(1-L)^d$ represents the fractional differencing lag operator.

The ARFIMA model is stationary and invertible if $-0.5 < d < 0.5$, and the effect of shocks ε_t decays at a slow rate to zero. The process has a short memory if *d = 0,* where the effect of shocks declines geometrically. A unit root process is defined if *d = 1*. The model has a persistent temporal dependence among distant observations or has long memory process if *0 < d < 0.5*. Furthermore, the process has intermediate memory or has anti-persistence if *-0.5 < d < 0,* the process is non-stationary if $d \geq 0.5$. And a stationary but a noninvertible process is existent if $d \leq -0.5$, making the time-series impossible to model by any AR process.

The FIGARCH model was proposed by Baillie et al. (1996) and provides more flexibility because it can differentiate short memory and long memory processes in returns and volatility. The model extends the traditional GARCH model to include fractional integration, which allows the differencing parameter *d* in the conditional variance to be a non-integer. FIGARCH (p,d,q) model can be expressed as:

$$[\phi(L)(1-L)^d]\varepsilon_t^2 = \omega + [1-\beta(L)](\varepsilon_t^2 - \sigma_t^2), \qquad (3)$$

Or

$$\sigma_t^2 = \omega + \beta(L)\sigma_t^2 + [1-\beta(L)]\varepsilon_t^2 - \varphi(L)(1-L)^d \varepsilon_t^2,$$
$$= \omega[1-L]^{-L} + \lambda(L)\varepsilon_t^2,$$

Where *(L)* represents the lag-operator, λ *(L)* = $\sum_{i=1}^{\infty} \lambda_i L^i$ and 0 ≤ *d* ≤ 1. λ *(L)* denotes an infinite summation that has to be truncated in applications, and $(1-L)^d$ represents the fractional differencing operator.

The HYGARCH model was suggested by Davidson (2004) as an improvement of the FIGARCH model. The model introduced weights in the difference operator to also capture the long-memory in conditional volatilities. The HYGARCH model also analyzes whether the non-stationarity of the FIGARCH model holds. The HYGARCH model can be expressed as follows:

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1} p(L)[1+\alpha\{(1-L)^d\}]\}\varepsilon_t^2. \quad (4)$$

The model can become a generalized FIGARCH when $\alpha = 1$, and nests to GARCH when $\alpha = 0$.

3. EMPIRICAL RESULTS

Table 1 illustrates that the average returns of Asian EM ETFs during the data period are mostly positive, except for Russia's RSX ETF and Vietnam's VNM ETF, which experienced average losses of -0.020 and -0.013, respectively. RSX ETF also posted the highest volatility with a 1.512 standard deviation, while India's ICN ETF has the lowest with 0.415. Among the EM ETFs under study, the RSX ETF is considered to be consistent with the Modern Portfolio Theory of Markowitz (1952), which posted the highest dispersion of returns and volatility. Four Asian EM ETFs (i.e., EWM, GXC, ICN and IDX) are positively skewed and the remaining three ETFs (i.e., RXS, THD and VNM) are negatively skewed. The kurtosis coefficients of all ETFs have leptokurtic distributions, wherein the data have generally more acute peak around the mean and fatter tails. The Jarque-Bera statistic for residual normality shows that Asian EM ETFs returns are under a non-normal distribution assumption.

Table 2 demonstrates the initial filtering done by the study. The Augmented Dickey-Fuller (ADF) test diagnosed a stationary data for all the Asian EM ETFs. The minimum value of the Akaike Information Criterion identified the orders of the ARMA and EGARCH model filters to eliminate serial correlation and inconstant variance problems, respectively. All ETF return samples have no serial correlation based on the results of the Lagrange Multiplier test. No heteroskedasticity problem was also established based on the ARCH-LM process; the test also shows that the study can apply the

ARCH process in the sample after the final filter test.

Table 3 features the findings for the ARFIMA, ARFIMA-FIGARCH and ARFIMA-HYGARCH models. The ARFIMA model shows that the SPDR S&P China ETF (GXC) and Wisdom Tree Indian Rupee Fund (ICN) structures are also stationary consistent with the initial findings of the ADF test. GXC and ICN ETFs exhibit intermediate memory or the so-called anti-persistent properties. These results mean that the persistency of having positive or negative returns in a particular time is weak and will more likely change course in the next trading period. Chen and Diaz (2014) found similar findings when they studied the anti-persistence of the Philippine stock market after the subprime mortgage crisis. Intermediate property of financial time-series returns warns investors to be always on the look-out for changes in the market trends caused by fundamental factors.

This study also finds persistent temporal dependence in the volatility structures of most Asian EM ETFs, except for Market Vectors Indonesia Index (IDX) using the ARFIMA-FIGARCH models. The long memory property present in the volatility structures of the ETFs under study is a possible sign of market inefficiency and investors may experience excess returns in the long-term by having a “hold” strategy on these Asian EM ETFs investments. The existence of persistent temporal dependence in the volatility contradicts the weak-form market efficiency hypothesis of Fama (1970). These results of long memory process in the volatility are consistent with the papers of Tan and Khan (2010) when they studied Malaysian stock markets, and Chen and Diaz (2013) when they compared Green and Non-green ETFs.

The ARFIMA-HYGARCH models also find consistent intermediate memory property of the GXC ETF, which means that its tendency to mean revert cannot be discounted, because of its anti-persistent property. This research also finds long memory properties in the volatility structures of most Asian EM ETFs, except for Market Vectors Vietnam ETF (VNM). This result is consistent with Cao (2009) when the author showed the long memory property of China's Shanghai and Shenzhen stock markets. The alpha (*a*) value, which defines the uniqueness of the HYGARCH model to FIGARCH and GARCH models are all insignificant. Nevertheless, the log-likelihood values of the seven Asian EM ETFs consistently points to the combined ARFIMA-HYGARCH models as the best fitting model to characterize the data over the ARFIMA and ARFIMA-FIGARCH models.

4. CONCLUSIONS AND LIMITATIONS

Finding persistent temporal dependence between distant returns and volatility of emerging economies time-series is of great significance because of their potential as long-term investments. This study provides evidences in the long-memory properties of return and volatility seven Asian EMs ETFs. This paper finds that the ARFIMA and ARFIMA-HYGARCH models showed that GXC and ICN ETFs exhibit intermediate memory properties, which mean that the having positive or negative trends in a particular time will more likely change course in the succeeding trading periods given sudden market shocks. In utilizing the ARFIMA-FIGARCH models, this research finds long-memory properties in the volatility structures of most Asian EM ETFs, except for Market Vectors Indonesia Index (IDX). The ARFIMA-HYGARCH models also find strong persistent temporal dependence in the volatility structures of most Asian EM ETFs, except for Market Vectors Vietnam ETF (VNM). Furthermore, the log-likelihood values of the seven Asian EM ETFs are the highest for the ARFIMA-HYGARCH models, which means that it is the best fitting set of models to characterize the time-series data compared to the ARFIMA and ARFIMA-FIGARCH models.

The study offers an initial step to determine the predictability of seven Asian EM ETFs. A viable extension of this research is to identify the type of forecast (i.e., one-step ahead, two-step ahead forecasts, and possible extensions) appropriate for the data sample. The recent Sub-prime mortgage crisis could have been a good opportunity for structural break tests however; this paper was limited in the recent inception of ETFs under study. The research also focused with Asian EM ETFs, which were subjected to fractional integration, future studies can also apply other methodologies using other types of ETFs or other relevant investment instrument.

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Table 1: The Sample Size and Period of Seven Asian EM ETFs

List of Asian emerging markets ETFs	Start of Data	Obs	Mean	Std. Dev.	Skew.	Kurt.	J-Bera
iShares MSCI Malaysia Index Fund (EWM)	2008-4-02	1258	0.007321	0.6286	0.0509	3.4851	637.20***
SPDR S&P China ETF (GXC)	2008-4-02	1449	0.001823	1.0660	0.3087	8.9619	4872.1***
Wisdom Tree Indian Rupee Fund (ICN)	2008-5-23	1220	0.000469	0.4148	0.5899	22.853	26620***
Market Vectors Indonesia Index (IDX)	2009-1-21	1054	0.056281	0.9049	0.1139	2.8006	346.74***
Market Vectors Russia ETF (RSX)	2008-4-02	1258	-0.019551	1.5115	-0.4489	9.0375	4323.5***
iShares MSCI Thailand Investable Market Index Fund (THD)	2008-4-02	1243	0.019924	0.9603	-0.2868	5.1295	1379.7***
Market Vectors Vietnam ETF (VNM)	2009-8-17	1102	-0.012829	0.8161	-0.1390	1.0199	51.308***

Source: Yahoo Finance; http://etfdb.com/etfdb-category/emerging-markets-equities/

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 2: Summary Statistics of ARMA and EGARCH filtering

List of Asian EM ETFs	ADF	ARMA	AIC	LM test	ARCH-LM	EGARCH	AIC	ARCH-LM
EWM	-42.3994***	(1,2)	1.8798	0.236475	121.2391 (0.0000)***	(3,2)	1.5345	2.5975 (0.2729)
GXC	-19.3414***	(3,3)	2.9231	1.615338	294.2034 (0.0000)***	(3,2)	2.3380	4.2917 (0.1170)
ICN	-23.0981***	(2,3)	1.0459	3.710136	171.6569 (0.0000) ***	(3,3)	0.5886	8.9307 (0.0115)
IDX	-17.4146***	(3,3)	2.6304	2.877948	66.6525 (0.0000) ***	(3,1)	2.3389	2.9712 (0.2264)
RSX	-27.3490***	(2,2)	3.6525	7.013959	218.4240 (0.0000) ***	(3,2)	2.9447	3.2055 (0.2013)
THD	-40.8345***	(2,3)	2.7385	0.081348	139.1052 (0.0000) ***	(3,3)	2.3331	0.1976 (0.9059)
VNM	-14.3941***	(2,3)	2.4217	0.338294	18.9644 (0.0001) ***	(2,3)	2.3633	1.0013 (0.6061)

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 3: Summary Statistics of ARFIMA, ARFIMA-FIGARCH and ARFIMA-HYGARCH models

Asian EMETFs	ARFIMA			ARFIMA-FIGARCH				ARFIMA-HYGARCH				
	d-coeff.	ARMA	AIC	d-coeff.	ARCH	d-coeff.	AIC	d-coeff.	ARCH	d-coeff.	Alpha	AIC
EWM	0.0215 (0.470)	(3,2)	1.8779	-0.0237 (0.5548)	(3,0)	0.9943*** (0.0000)	1.5614	-0.0243 (0.5712)	(1,2)	1.0345*** (0.0000)	-0.0080 (0.3339)	1.5601
GXC	-0.0599 (0.088)	(2,3)	2.9289	-0.0623 (0.1599)	(3,3)	1.0161*** (0.0000)	2.3513	-0.0974 (0.0142)	(3,3)	1.1122*** (0.0000)	-0.0073 (0.4532)	2.3466
ICN	-0.0850 (0.012)**	(3,2)	1.0531	-0.0487 (0.4474)	(3,2)	0.6550*** (0.0000)	0.5875	-0.0381 (0.5883)	(3,3)	0.6186*** (0.0000)	0.0125 (0.7916)	0.5894
IDX	0.1332 (0.145)	(3,1)	2.6400	0.0777 (0.2899)	(2,3)	0.5995 (0.1347)	2.3536	0.0909 (0.2349)	(3,3)	0.8059*** (0.0000)	-0.0374 (0.1068)	2.3551
RSX	-0.0348 (0.180)	(3,3)	3.6613	0.1399 (0.2255)	(1,2)	0.7881*** (0.0043)	2.9552	0.1380 (0.2449)	(1,3)	0.7020*** (0.0000)	-0.0187 (0.4308)	2.9575
THD	0.0165 (0.640)	(3,3)	2.7388	0.0198 (0.6817)	(1,2)	0.6110*** (0.0002)	2.3445	0.0191 (0.6930)	(2,2)	0.5935*** (0.0020)	0.0003 (0.9931)	2.3472

VNM	-0.0104 (0.797)	(1,0)	2.4381	-0.0391 (0.4880)	(1,1)	0.3404*** (0.0024)	2.3745	-0.0550 (0.3061)	(0,1)	0.0924 (0.5114)	0.7777 (0.5422)	2.3749

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.